A Robotic-Based Framework for Quantifying Surface Cracks of Concrete Shear Walls

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ABSTRACT

The inherently subjective and manual nature of current structural assessment procedures undermines the reliability of such practices. As a result, researchers are using artificial intelligence and robots to encourage autonomy and create methods that are more objective and less biased. Robots are equipped with cameras and sensors to collect information about the structure, such as images of the crack patterns of concrete structures. In this paper, a robotic framework is proposed to utilize the collected images of reinforced concrete shear walls (RCSWs) with crack patterns, and then those images are used to quantify the level of damage. Crack pattern images are from the load steps of a quasi-static test on an RCSW. To quantify the extent of damage, crack patterns are first converted to a mathematical representation, a graph. Next, a machine learning algorithm is trained to predict the energy dissipated during each load cycle based on the graphs. Results reveal that the presented graph-based damage quantification method is able to quantify the level of structural damage. High R^2 scores of the machine learning regression (above 0.98) attest to the success of the proposed robotic-based framework.

INTRODUCTION

As part of nondestructive evaluation (NDE), one can determine how much damage has been caused to a structure. Man-made (e.g., earthquakes caused by fracking, increased loads, etc.) and natural (hurricanes, tsunamis, tornados, earthquakes, floods, etc.) hazards are increasingly threatening infrastructures' safety and resilience, which makes the rapid after-event serviceability assessment essential. However, earlier human-based assessment methods are error-prone and pose a risk to the inspector's life [1,2]. As a result, robotics and artificial intelligence (AI) can revolutionize the way we maintain infrastructures. In order to overcome these deficiencies and risks, researchers have used AI [3,4] and robots [5–7].

This study presents a robotic framework for the analysis of reinforced concrete shear walls (RCSWs) with cracks. The robotic framework uses the collected crack pattern

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images of an RCSW. The focus of this study is on the quantification module of the framework, for which, the digitized crack pattern images are transformed into graphs [8]. The novelty of this paper is using graph theory, which is the mathematical form of representing crack patterns. Graph theory is then applied to extract information and quantify the damage using machine learning (ML). Specifically, the prediction estimates the energy dissipated during each load cycle as a damage index. The flow of information in the framework is illustrated in Figure 1. In the proposed framework, a structural system is considered that used to be inspected by humans and now is inspected using robots. After the robotic-based image collection, the analysis of the collected data is automated using the mathematics of graph theory by converting the crack patterns to their representative graph. Graph representations pave the way for machine learning analysis by introducing graph features. Graph features are numerical values with which images of the crack patterns are represented. Using the extracted graph features, the proposed quantification module of the framework predicts the damage index of the structure by using machine learning. Eventually, the results of the machine learning predictions can be used for the decision support system as the level of structural damage is quantified.

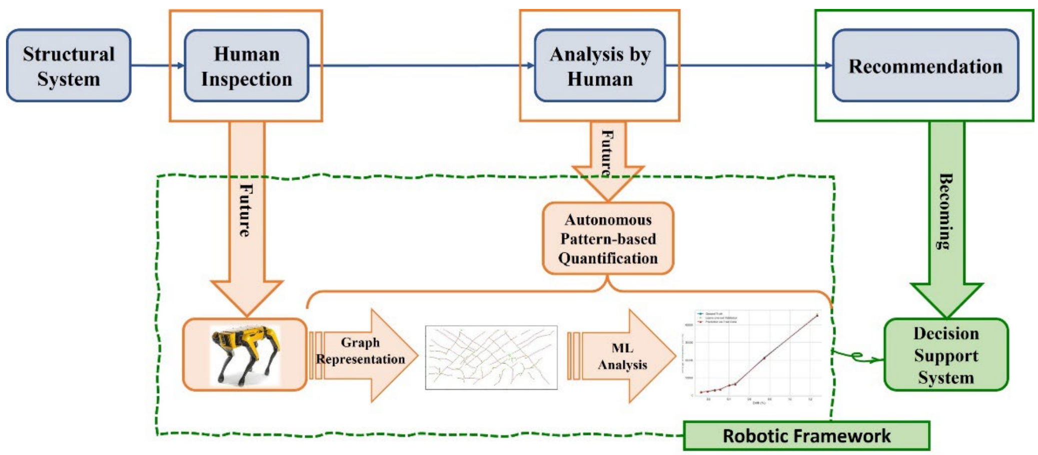
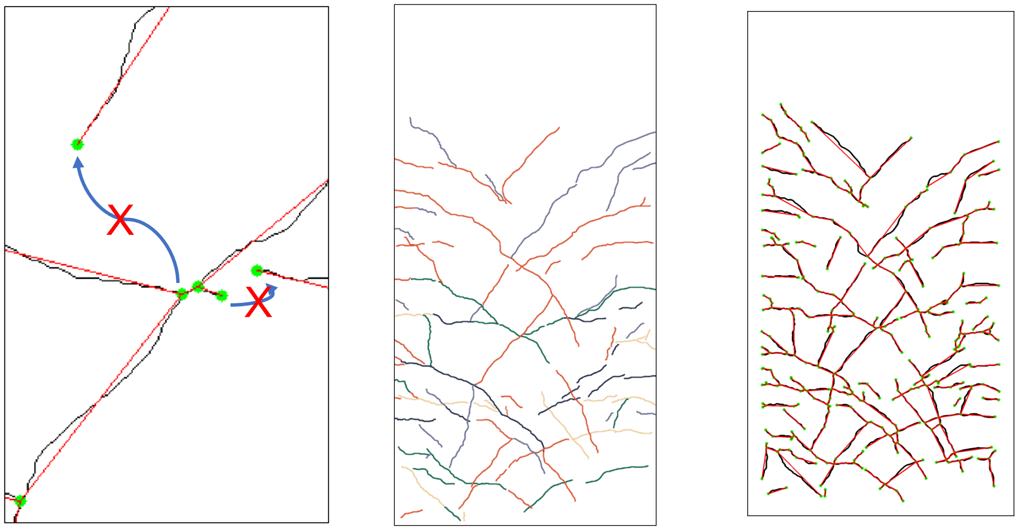


Figure 1. The flow of information in the proposed robotic framework

METHODOLOGY: CRACK-TO-GRAPH CONVERSION

With the Shi-Tomasi [9] corner detection algorithm, crack patterns on the RCSW can be converted into graphs. Using this algorithm, crack intersections and endpoints can be identified in images. Corners are marked as vertex points in the graph and connected based on the pattern of cracks on the concrete surface. An AI-based algorithm (breadth-first search) is adapted to track cracks pixel by pixel. Figure 2(a) provides a visual representation of how corners are connected to form the graph. The corners (vertices) are shown in green. The corners that should be connected to each other are connected with a red line based on the crack pattern in black. However, the corners that should not be connected to each other are pointed out with a blue arrow and a red cross.

Additionally, Figure 2(b) depicts the crack patterns present on an RCSW's surface, while Figure 2(c) illustrates the representative graph of the crack pattern.



a) The concept of corner connection

b) Crack patterns of the RCSW from load step 6 (each color represents the crack pattern from a certain load step)

c) The representative graph of the crack pattern

Figure 2. Crack-to-graph conversion: from concept (a) to the representative graph (c)

EXPERIMENTAL SETUP

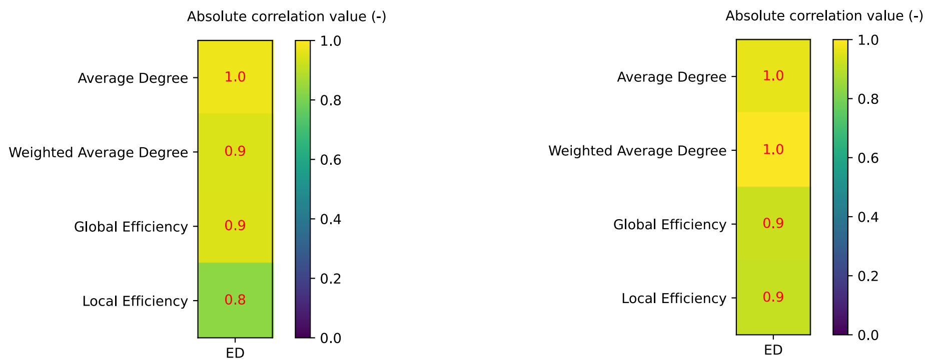
The proposed method was verified using the experimental data from an RCSW with 305 cm in height, 152 cm in width, and 15 cm in thickness [10]. The wall aspect ratio was 2.00 and the concrete strength (f_c') was 26 MPa (see Table I for all RCSW properties). The wall was subjected to quasi-static loading protocols and the images of the crack patterns were captured at each load cycle, with crack pattern images used as the basis of analysis in this study.

TABLE I. Reinforced concrete shear wall (RCSW) characteristics [10]

Characteristics	**RCSW**
Height (cm)	305
Width (cm)	152
Thickness (cm)	15
Aspect ratio (h/l)	2.00
Wall f_c' (MPa)	26

CORRELATION ANALYSIS AND MACHINE LEARNING PREDICTION

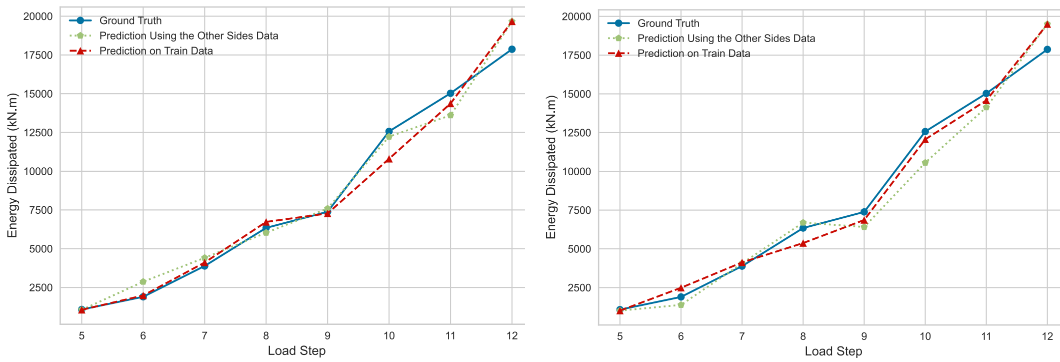
Before utilizing machine learning to predict the damage index, a linear Pearson correlation analysis [11] is performed on the graph and mechanical features to determine the relationship between them. In this paper, the mechanical feature is the energy dissipated (enclosed area under the hysteresis loop at each load cycle) from a quasi-static test conducted on the RCSW. The results of the Pearson correlation analysis revealed a strong correlation between the graph features and the damage index, as indicated by the high correlation values. As illustrated in Figure 3, the correlation values are above 80%. The high correlation values indicate that the graph features hold meaningful information but require further interpretation for deeper analysis.



a) RCSW - North b) RCSW - South

Figure 3. Correlation analysis between graph features of the RCSW and the energy dissipated (ED)

A linear regression machine learning approach is applied to the data in order to test the interpretability of graph features. The objective is to use graph features to determine the predictability of the energy dissipated. Utilizing the linear regression algorithm, the north face mechanical feature was predicted with a 3.6% error rate, and the south face with a 4.1% error rate. For the machine learning application, the available data was limited, so overfitting was prevented by using data from the other side of the wall as well. As part of this process, the data from one side was used to train the model, and the data from the other side was used to verify the model. As a result, the model accurately predicted the energy dissipated on both the north and south faces with an error of 5% using the other side's data. As shown in Figure 4, the machine learning algorithm predicted the energy dissipated by the RCSW from graph features. The results showed that the proposed graph-based damage assessment method was able to accurately determine the amount of structural damage.



a) RCSW - North b) RCSW - South

Figure 4. Machine learning prediction

CONCLUSIONS

The robustness of the proposed robotic-based framework was established through high correlation values, paving the way for further exploration into the relationship between crack patterns and graph theory. The use of machine learning also demonstrated that graph features can be used to quantify damage, as the relationship between the mechanical and graph features allows the graph features to serve as a representation of the mechanical features for structure evaluation. Additionally, the method's ability to quickly process and calculate results makes it suitable for prompt damage assessment following sudden incidents. For future studies, it is of great interest to apply the method to larger data sets using the proposed robotic framework. The performance of the robotic framework can be explored on different concrete surface conditions (e.g., wet surface, and coloration to name a few).

ACKNOWLEDGEMENT

The authors acknowledge Dr. Pinar Okumus and Dr. Sina Basereh from the University at Buffalo, State University of New York for their data sharing under the National Science Foundation Grant No. 1663063. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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